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ASYMMETRIC VOLATILITY DYNAMICS: EVIDENCE FROM THE ISTANBUL STOCK EXCHANGE*

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ABSTRACT

This paper considers estimating the conditional mean and variance from a single-equation dynamic model with the mean following an ARMA $\#(1,7)$ process, and the conditional variance with time-dependent conditional heteroskedasticity as represented by ARCH models. The volatility is measured by a linear GARCH and an EGARCH process. Our results suggests that EGARCH provides better estimates than a linear standard GARCH model. The EGARCH also can capture most of the asymmetry, supporting the hypothesis that negative return shocks cause higher volatility than positive return shocks at the Istanbul Stock Exchange.

1. INTRODUCTION

This paper examines Turkish stock returns from 1989 to end-1996, focusing especially on three episodes of high volatility associated with populist elections: the stock price slump in 1991 linked to Gulf crisis and the resulting economic stagnation and 1991 elections, the surge in prices in 1993 due to the economic boom followed by the Turkish economic highest financial crisis and 1994 local elections, and finally 1995 economic recovery stabilization efforts sustained up to September 1995 with the announcement of early elections in December 1995.

To help examine these aspects of stock price volatility at the Istanbul Stock Exchange (ISE), a generalized conditional heteroskedasticity model (GARCH) and alternatively an exponentially generalized conditional heteroskedasticity model (EGARCH), which allows the conditional variance to be time-variant, is estimated. The analysis brings out several important features about the dynamic behavior of Turkish stock prices.

There are several ways of dealing with changing volatility: these are nonlinear models that can be grouped as parametric and nonparametric models. One can use nonparametric estimation techniques to capture a wide range of nonlinearities without any particular specification of the nonlinear relation. They require few assumptions about the nature of the nonlinearities but their estimation is highly data intensive and generally not effective for smaller sample sizes and they are usually prone to overfitting (Lo and MacKinlay, 1997).

In applied work, It has been frequently demonstrated that parametric Arch models are able to represent the majority of financial time series (Bera and Higgins, 1993).

Garch models have been extensively used in finance because they provide a flexible and parsimonious approximation to conditional variance dynamics, in the same way that ARMA models provide a flexible and parsimonious approximation to conditional mean dynamics. In such models, an infinite ordered distributed lag operator polynomial can be approximated as the ratio of two finite, low-ordered lag operator polynomials (Diebold and Lopez, 1995).

They were first introduced by Engle (1982), who suggested a new class of models where the conditional variance (h_t) is a function of past squared residuals (ϵ_t^2 's).

This means that the predictable volatility is dependent on past news. The model he proposes is the ARCH model of order p :

$$h_t = w + \sum_{i=1}^p \alpha_i + \epsilon_{t-i}^2 \quad (1)$$

where $\alpha_1, \alpha_2, \alpha_3, \dots, \alpha_p$ and w are constant parameters. The effect of the ϵ discrepancy on the return i periods ago ($i < p$) on current volatility is governed by the parameter α_i . The older the news, the less effect it has on current volatility.

* I am especially grateful for insightful and detailed comments and suggestions of the two referees.

Bollerslev generalizes the ARCH(p) model to the GARCH(p, q) model such that

$$h_t = w + \sum_{i=1}^p \alpha_i + \varepsilon_{t-1}^2 + \sum_{i=1}^q \beta_i h_{t-i} \quad (2)$$

where $\alpha_1, \alpha_2, \alpha_3, \dots, \alpha_p, \beta_1, \beta_2, \beta_3, \dots, \beta_q$, and w are constant parameters. In the GARCH(1,1) model the effect of a return shock on current volatility declines geometrically over time.

Empirically the GARCH(1,1) model has been very successful for the Istanbul Stock Exchange (Okay, 1998a).

Despite the apparent success of the Garch model, it cannot capture some important features of the data. The most interesting feature is the asymmetric effect discovered by Black (1976). The effect occurs when a bad news increases the predictability of volatility more than a good news of similar magnitude. This effect suggests that a symmetry constraint on the conditional variance function in past ε 's is inappropriate. The method that captures such asymmetric effects is the Exponential GARCH (EGARCH) model (Nelson, 1990).

$$\log(h_t) = C + q \left(\left| \varepsilon_{t-1} \right| / \sqrt{h_{t-1}} - \sqrt{2/\pi} \right) + P \log(h_{t-1}) + \lambda \left(\left| \varepsilon_{t-1} \right| / \sqrt{h_{t-1}} \right) \quad (3)$$

where C, λ, q, P , are constant parameters. The term $\left| \varepsilon_{t-1} \right| / \sqrt{h_{t-1}}$ included with a λ , is the asymmetric term indicating that positive return shocks generate less volatility than negative return shocks when λ is negative.

II.1. THE DATA

This paper is using monthly observations of the Istanbul Stock Exchange Composite index to examine the volatility. ISE is an equally-weighted index using closing prices. Monthly stock indices are obtained from the Center For Applied Research in Finance (CARF) of Boğaziçi University's database. The sample period is between January 1988 and December 1996. The closing index values are then used to calculate the log returns.

$$R_t = 100 [\log(p_t/p_{t-1})] \quad (4)$$

where p_t and R_t are ISE closing price and the log return of the ISE.

Statistical description of asymmetry shows that, equally-weighted Istanbul Stock Exchange index estimated by CARF shows a normal distribution with an excess negative kurtosis and negative skewness (Table 1). Large negative index returns are more common than large positive ones, so the index is negatively skewed. This explains why extreme stock movements are more common than would be expected (Okay, 1993).

Table 1 - Univariate Statistical Properties

Variable	First differences of the monthly log price changes of ISE Index
Period	January 1989 to December 1996
Sample Size	107 observations
Mean	20.11
Std.Deviation	22.56
Skewness	-0.024
Excess Kurtosis	-0.591
Maximum	71.24
Minimum	-32.16

Normality* Chi ² (2)	1.155
Probability	0.5613
Asymptotic form of normality test	1.5689

* Asymptotic form of normality is the Jarque-Bera statistic: $\text{skewness}^2 * n/6 + \text{kurtosis}^2 * n/24$, where n is the number of observations, requires large sample for the asymptotic $\text{Chi}^2(2)$ distribution to hold. The reported test statistic has a small-sample correction.

II.2. AUTOCORRELATION TESTS

Table 2 reports the autocorrelations and Box-Pierce Q-statistics for monthly stock returns from January, 1989 to December 1996. During this period, stock returns had a first-order autocorrelation $\rho(1)$ of 23.61 percent. Moreover, the Box-Pierce Q-statistic with six autocorrelations has a value of 16.04 which is significant at all conventional levels of significance. The autocorrelations seem to indicate a random series with some predictive power.

Next, the autocorrelations of the squared index returns were examined. The sample autocorrelations for the square of the series shows significant serial dependencies after the third lag. The Box-Pierce Q-statistic for the tenth-order serial correlations, $Q^2(10)$, in the squares suggests the presence of time-varying volatility.

The motivation behind examining the sample autocorrelations of squared returns lies in the fact that the squared returns provide a sufficient statistic for the variance of the process (Engle and Ng, 1993).

A preliminary economic investigation describing an autoregressive model for stock returns suggests the definite possibility that subtle nonlinearities may be present. The author therefore concludes that stock returns are significantly heteroskedastic in the sense that strong serial correlations in variances are present. One deals with this finding more completely via the use of ARCH models.

Table- 2- Autocorrelation in monthly stock index returns

	Sample Size	$\rho(1)$	$\rho(2)$	$\rho(3)$	$\rho(4)$	Q(6)	Q(12)	$Q^2(7)$	$Q^2(10)$
89:01-96:12	107	23.61	10.98	18.41	19.81	16.04 0.0135	34.44 0.0005	16.09 0.0242	17.03 0.0735

Autocorrelation coefficients (in percent) and Box-Pierce Q-statistic for CARF monthly equally weighted return index for the sample from January, 1989 to December 1996.

III. ESTIMATION OF TURKISH STOCK RETURN VOLATILITY: 1989 TO 1996

III.1. GARCH(1,1) MODEL ESTIMATION RESULTS

The autocorrelation structure present in the second order moments of the ISE index series, indicate some form of heteroskedasticity.

Since numerous studies have shown that stock market volatility is time-varying, (Poterba, 1986; Baillie and Bollerslev, 1989, among others), GARCH formulation is used to describe time-dependent conditional heteroskedasticity:

$$100 \Delta \log P_t = A_0 + A_1 100 \Delta \log P_{t-1} + \varepsilon_t + \theta \varepsilon_{t-7} \quad (5)$$

$$\varepsilon_t \mid \Omega_{t-1} \sim N(0, h_t)$$

$$h_t = C + q \varepsilon_{t-1}^2 + \text{Ph}_{t-1}$$

The model for the conditional mean and a GARCH process for the conditional variance was jointly estimated by the BHHH maximum likelihood approach. The algorithm used for the numerical optimization of the Maximum Likelihood is a two-step iterative procedure that combines a Genetic Algorithm (GA) with the Berndt, Hall, Hall and Hausman (BHHH) algorithm (Berndt et al, 1974). The most robust model based on log-likelihood values was where the conditional mean specified as an ARMA #(1,7) process with a constant and where the conditional variance

specified as a GARCH # (1,1) process. The model together with the test statistics is given in Table 3. The serial correlation is rejected for the standardized residuals at the lag 12, at the conventional significance levels (Q(12)). The sample autocorrelation function of squared residuals is asymptotically chi-squared distributed under the null hypothesis of no serial correlation ($Q^2(12)$). The null is accepted at the conventional significance level (5 percent). It indicates no presence of any serial correlation and the adequacy of the model. The residuals conditional on past information are assumed to be normally distributed.

The results are very interesting. The author finds significant positive autocorrelation for the index, with the positive θ 's indicative of market over-reactions in heavily traded assets. Secondly, a high value (about 0.9 or higher) of coefficient of the lagged conditional variance, P, shows that once volatility becomes higher, it tends to stay that way for a while. The volatility clustering is quite common in many asset prices; it is in fact a core of the GARCH specification.

All parameters in the conditional variance term are significant at 10 percent level, indicating support for the Garch # (1,1) model. Consistent with Bollerslev and Domowitz (1993) the author also finds evidence of an IGARCH model, with the coefficients $P+q$ approaching one for the CARF equally weighted ISE index without dividends. This means that today's volatility affects forecasts of volatility into then indefinite future. Furthermore the constant term in the conditional variance equation is positive indicating that there exists a nondegenerate stationary distribution for h_t . This shows that the model is strictly stationary but not generally covariance stationary.

Table 3- GARCH # (1,1) Model estimation results

	A0	A1	C	θ	q	P	Q(12)	$Q^2(12)$
Coeff	16.80	0.14	45.59	0.59	-0.18	1.07	8.34	9.61
P value	0.0000	0.1367	0.0904	0.0000	0.0018	0.0000	0.1383	0.0867
T-Stat	4.6428	1.4878	0.16931	7.8834	-3.1165	27.4749		
Logl	-301.33							

Logl is the value of the maximized log likelihood function

Q(12) denotes the Box-Pierce Q-statistic of the standardized residuals

$Q^2(12)$ denotes the Box-Pierce Q-statistic of the squared standardized residuals

III.2. EGARCH(1,1) MODEL ESTIMATION RESULTS

To obtain a feel for the leverage dynamics, the author examines the asymmetric effect given by the EGARCH (1,1) model $|\varepsilon_{t-1}| / \sqrt{h_{t-1}}$ term indicated by the parameter λ . This model is appealing because it becomes both strictly nonstationary and covariance nonstationary when $P+q = 1$, so it does not share the unusual statistical properties of the IGARCH(1,1) model.

$$100 \Delta \log P_t = A_0 + A_1 100 \Delta \log P_{t-1} + \varepsilon_t + \theta \varepsilon_{t-1} \quad (6)$$

$$\varepsilon_t | \Omega_{t-1} \sim N(0, h_t)$$

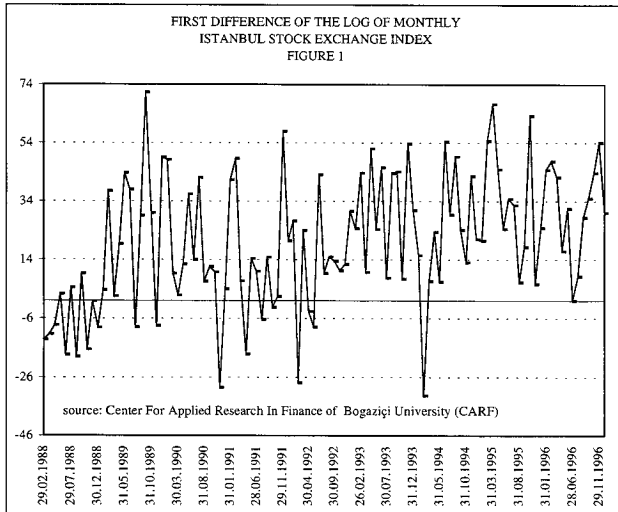
$$\log(h_t) = C + q(|\varepsilon_{t-1}| / \sqrt{h_{t-1}} - \sqrt{2/\pi}) + P \log(h_{t-1}) + \lambda(|\varepsilon_{t-1}| / \sqrt{h_{t-1}})$$

The model for the conditional mean and a EGARCH process for the conditional variance was jointly estimated by the BHHH maximum likelihood approach. The estimation results in Table 5 indicate that all parameters are significant with high levels of significance (1 percent level). The serial correlation is rejected for the standardized residuals at the lag 12, at the conventional significance levels (Q(12)). The sample autocorrelation function of squared residuals is asymptotically chi-squared distributed under the null hypothesis of no serial correlation ($Q^2(12)$). The null is accepted at the conventional significance level (1 percent). It indicates no presence of any serial correlation and the adequacy of the model. The residuals conditional on past information are assumed to be normally distributed.

The parameter corresponding to the $|\varepsilon_{t-1}| / \sqrt{h_{t-1}}$ term is significant and negative using robust errors. This result is consistent with the hypothesis that negative return shocks cause higher volatility than positive return shocks (Engle & Ng, 1993). One can also see that the standard GARCH(1,1) has a lower log-likelihood than the leverage

EGARCH(1,1) model. The EGARCH seem to outperform the standard GARCH(1,1) model in capturing the dynamic behavior of the Turkish stock returns.

The conditional variance-- the predictable element of volatility--of the first differences of the log of stock prices is given in Figure 2 (compare with the actual volatility in Figure 1). As can be inferred, the predictable element of volatility is predominant, and some informational content of the model is suggested by flares in the conditional variance in the early 1990s associated with increased volatility.



The first large fluctuation at the beginning of 1989 is due to the positive impact of liberalization of capital movements on the Turkish economy. From July 1988, foreign investors were admitted to the Turkish capital market, and starting from June 1989, foreign investment funds were allowed to operate. In August 1989, Turkish residents were given permission to purchase foreign securities freely, as well as foreign currency. The financial reform seems to have succeeded in stimulating private financial savings, as well as the depth of financial markets (observations 9-18). However, in the period from 1990 through late 1991, the estimated conditional variance declined and fluctuated associated with the price stagnation of 1991 as a result of the Gulf crisis and domestic political uncertainties (Figure 2, observations 36-45). Thereafter, the volatility increased, although not to the levels experienced during mid-1991 (observations 45-54). The second hop of the estimated conditional variance during 1993-1994 shows the economic boom survived and the resulting financial crisis (observations 54-67). The last important remarkable jump of the conditional variance shows the 1995 economic recovery followed by a decreasing trend indicative of the economic destruction of the early December 1995 elections (observations 87-95).

The conditional variance series produced by best model, the EGARCH, have the highest variation over time (Table 7). The estimated conditional variance ranges from a low of 13.859 to a high of 2298.139 compared to 94.58 and 766.222 under the standard GARCH model. The standard error of the EGARCH conditional variance, 389.660, is higher than (40 points) than that of the standard GARCH model and is lower than the squared residual itself.

The fact that the unconditional variance of the EGARCH conditional variance is smaller than the unconditional variance of the squared residual can be interpreted as evidence for the EGARCH model (Engle & Ng, 1993). Consequently, the EGARCH model, which also has higher log-likelihood than the GARCH model, might be a more reasonable model to use.

Table 4- EGARCH # (1,1) Model estimation results

	A0	C	P	q	λ	A ₁	θ	Q(12)	Q ² (12)
Coeff	18.51	2.29	0.60	-1.31	-0.20	0.17	0.50	6.688	14.56
P value	0.0000	0.0000	0.0000	0.0000	0.0011	0.0000	0.0000	0.2448	0.0123
St. error	2.0735	0.0212	0.0021	0.0755	0.0604	0.0282	0.01812		
T-Stat	8.9296	107.93	287.20	-17.354	-3.2571	6.0223	27.7081		
Logl	-298.19								

Logl is the value of the maximized log likelihood function

Q(12) denotes the Box-Pierce Q-statistic of the standardized residuals

Q²(12) denotes the Box-Pierce Q-statistic of the squared standardized residuals

III.3. SIGN BIAS AND SIZE TEST RESULTS

These tests examine whether one can predict the squared normalized residual by some variables observed in the past which are not included in the volatility model being used. If these variables can predict the squared normalized residual, then the variance model is misspecified (Engle and Ng, 1993). The sign bias test examines the impact of positive and negative return shocks on volatility, not predicted by the model under consideration.

The negative size bias test focuses on the different effects that large and small negative return shocks have on volatility which is not predicted by the volatility model. The positive size bias test focuses on the different impacts that large and small positive return shocks may have on volatility, which are not explained by the volatility models : GARCH and EGARCH (Table 5).

Diagnostic test results about the ISE index indicate that the test statistics are not significant for both models, increasing the reliance of the models.

Table 5- Sign Bias and Size Test results for the GARCH and EGARCH Models

	Sign Bias Test	Negative Size Bias Test	Positive Size Bias Test	Joint Test
GARCH(1,1)	-0.7125	-0.209	-1.1998	0.5125
P value	0.4782	0.7871	0.2337	0.6751
EGARCH(1,1)	0.1378	-0.4016	0.3922	0.1465
P value	0.8907	0.6891	0.6960	0.9316

$$\text{Squared Standardized Residuals} = a + bS_{t-1}^- + cS_{t-1}^+ \varepsilon_{t-1} + dS_{t-1}^+ \varepsilon_{t-1} + e_t$$

S_{t-1}^- is a dummy variable that takes a value of one when ε_{t-1} is negative and zero otherwise.

III.4. DISCUSSIONS

Volatility is measuring the risk of stock market investment: the most important function of the stock market is to raise capital for corporations. If stock prices rationally reflect fundamental values, the stock market can then serve as a forecasting mechanism for firms and investors to guide the process of capital allocation. If, however, stock prices substantially deviate from fundamentals, as, for example, when they are largely driven by fads and noise trading (Shiller 1984, Summers 1986), or if the stock market price is too volatile, then investors may be less willing to hold equities, which tend to raise the cost of capital and depress investment.

Advanced research points to the fact that managers will take market volatility into account when they make investment decisions in US. There is evidence for the negative relationship between the stock market volatility and fixed investment. Large stock market price fluctuations are related to low growth in real fixed investment (Hu, 1995). In Turkey, stock market volatility may have led to a reduction, in the capital stock and hence log-run productivity and income growth. A more stable stock market will better serve as the forecasting mechanism for the economy as well as fulfill its role in channeling savings into capital investment (Okay, 1998b).

The lack of efficiency at the ISE may stimulate the increasing role public policy has in stabilizing the stock market (Okay, 1998a), however in the absence of a causal link here, it should be stressed that these results are insufficient to justify any proposed direct policy interventions. These tasks await further research.

On the other hand, policymakers also need to recognize that financial volatility, is not a bad thing but is rather part of how financial markets operate. Rather than worry about financial volatility in general, policymakers should be aware of when specific changes in asset prices might leave financial systems more vulnerable to financial instability.

Turkey is an emerging market economy with a high and variable inflation. Information about private firms is harder to collect than in industrialized economies and not surprisingly, securities markets therefore play a smaller role. The greater difficulty of acquiring information on private firms, makes banks even more important in the financial system of our country, and the barriers of information collection are so great that the dominance of banks will continue for the foreseeable future. Furthermore, It is not clear that higher volatilities of asset prices are more important factor promoting financial instability. There are many episodes of high asset price volatility in which there are no manifestations of financial instability (1990 Gulf Crisis, 1995 Early elections). A historical analysis of the financial crises of the Turkish economic history indicates that serious examples of financial instability are always associated with substantial deteriorations in the balance sheets of firms, households and banks. Thus, increased financial volatility that is not linked to deterioration in balance sheets is unlikely to produce financial instability which has harmful effects on the economy (Okay, 1998b). The large fluctuations cannot be fully explained by the macroeconomic fluctuations such as inflationary money growth and excess consumption (Schwert, 1989). They may be generated by trading activity (French and Roll, 1986) as well as by political risk.

Stock market engineering makes volatility desirable in a rising market: to the extent that volatility is not perfectly correlated with loss, predictable volatility - a forecast of the direction of the market- is a proof of the violation of the random walk hypothesis.

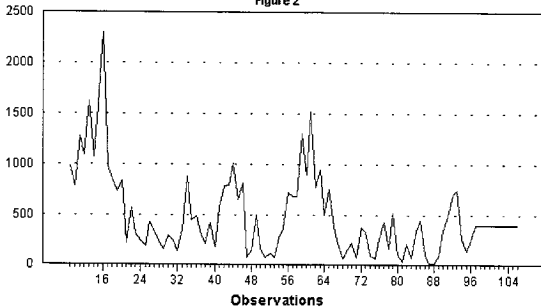
Table 6 - Summary Statistics of the Conditional Variance Estimates

	Mean	Std.Error	Min.	Max.	Skew.	Kurto.
U^2	374.064	492.943	0.034	3231.858	2.61	10.38
(CV)GARCH	346.906	135.386	94.588	766.222	0.90	1.76
(CV)EGARCH	483.133	404.555	13.852	2298.1392	1.69	3.92

The statistic "Skew" is the coefficient of skewness and the statistic "Kurto" is the coefficient of kurtosis. For a standard normal random variable, the value of skewness is 0 and the value of kurtosis is 3. U^2 is the squared unpredictable residual obtained from the Box-Jenkins estimation of the ARMA (1,7) of the conditional mean of the ISE. CV is the conditional variance of the GARCH and EGARCH models as indicated in Tables 3,4.

Estimated Conditional Variance of the ISE Equally Weighted Index using an EGARCH

Figure 2



IV. CONCLUSION

Both the GARCH and the EGARCH models perform well to explain the dynamic volatility of the ISE. But the EGARCH model performs better than the GARCH model with highly significant coefficients and takes account of the asymmetric behavior of the Istanbul Stock Exchange to support the hypothesis that negative return shocks cause higher volatility than positive return shocks (Engle & Ng, 1993). The coefficients $P+q$ of the GARCH model approaches one for the CARF equally weighted ISE index and finds evidence of an IGARCH model. Since the constant term in the conditional variance equation is positive, it points to a model strictly stationary but not generally covariance stationary. However EGARCH model is appealing because it becomes both strictly nonstationary and covariance nonstationary when $P+q = 1$, so it does not share the unusual statistical properties of the IGARCH(1,1) model. Consequently, the EGARCH model, which also has higher log-likelihood than the GARCH model, might be a more reasonable model to use.

The lack of efficiency at the ISE may stimulate the increasing role of public policy in stabilizing the stock market, however in the absence of an established causal link here, it should be stressed that these results are insufficient to justify any proposed direct policy interventions. These tasks await further research.

Policymakers need to recognize that financial volatility, is not a bad thing but is rather part of how financial markets operate. Rather than worry about financial volatility in general, policymakers should be aware of when specific changes in asset prices might leave financial systems more vulnerable to financial instability.

Stock market engineering makes volatility desirable in a rising market: to the extent that volatility is not perfectly correlated with loss, predictable volatility - a forecast of the direction of the market- is a proof of the violation of the random walk hypothesis.

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